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# Internet access and its role on educational inequality during the COVID-19 pandemic

Özge Korkmaz [a], Elif Erer [b], Deniz Erer [b,*]

[a] *Malatya Turgut Özal University, Faculty of Social Sciences and Humanities, Department of Management Information System, Yeşilyurt, Malatya, Turkey*
[b] *Independent Researcher, Izmir, Turkey*

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A B S T R A C T

This study investigates the determinants of Internet access and its effect on educational inequality in OECD countries during the period of the Covid-19 pandemic. The spatial panel data model is used to include the neighborhood in the model relating to educational inequality. The findings from the study reveal that despite the increase in Internet access during the Covid-19 period, the response to the pandemic has caused education inequalities. Furthermore, economic development indicators are effective in increasing Internet access and reducing educational inequality. Finally, the study shows that, as improvements in income levels can increase Internet access, which results in a reduction in educational inequality.

## 1. Introduction

Educational inequality reflects that children under the national average are disadvantaged academically because of lacking the same level of skills in society (Bruckauf & Chzhen, 2016). In Townsends' study on poverty (1979) educational inequality is defined as '*so seriously below those commanded by the average individual or family that they are, in effect, excluded from ordinary living patterns, customs, and activities*.

Achieving equality in education, which is one of the crucial indicators that affect sustainable development, is essential, particularly in the ways it develops human capital and provides individuals equal opportunities in the marketplace (Brighouse et al., 2010; Wilkinson and Pickett, 2010; Baker et al., 2016). However, educational inequality deepens economic inequalities, which ultimately hinders long-term economic welfare (Guo, 2006; Shindo, 2010).

Bourdieu's capital theory outlined in Bourdieu (1990) suggests that some types of Internet access will better assist individuals to attain meaningful economic, social and cultural capital and advance their education, career, and social standing. According to this view, the Internet can be used for two purposes. The first is capital-enhancing and uses resources to reach educational goals and develop their physical and mental health. The second type of Internet use is for leisure and entertainment (van Deursen and van Djik, 2014).

Bourdieu's study on social inequalities assumes that individuals incline to improve their skills and abilities highlighting their social

* Corresponding author.
*E-mail addresses:* ozge.korkmaz@ozal.edu.tr (Ö. Korkmaz), elif_erer_@hotmail.com (E. Erer), denizerer@hotmail.com (D. Erer).

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standing. Thus, these inclinations tend to reestablish and solidify existing advantages and disadvantages (Bourdieu, 1990). According to Bourdieu's theory of Internet access, disadvantaged youth might be less likely. Therefore, they use the Internet to improve their education (Zhang, 2015). Reinhart et al. (2011) indicate that the most of students from low-income families lacked institutional support to access technology and that disadvantaged students that lack technological support and resources might be less likely to access the Internet for educational purposes. Fig. 1 shows Moran's I plots for the Internet access and educational inequality in OECD countries.

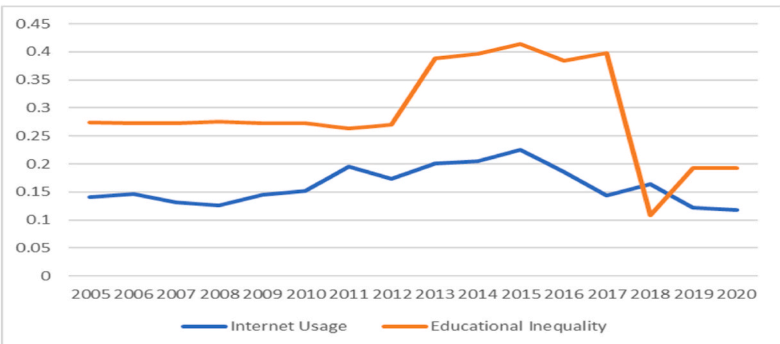
Robinson et al. (2015) and Büchi et al. (2016: 2704) stated that inequalities in accessing the Internet, especially for students with low-income families, can increase social and educational inequalities. The reports of UNICEF (2020c; 2020d; Blaskó & Schnepf, 2020) show that the Covid-19 pandemic has increased educational inequality. School closures rise inequalities among children from families with different socio-economic conditions (UNESCO, 2020a, 2020b; European Commission, 2020). Many school children worldwide, especially those in poorer households, have the limited opportunity to access the technologies such as the Internet, TVs, and computers, which lead to increased educational inequalities (UNICEF, 2020). By the report of UNICEF (2020), 31% of these children can not attain Internet-based remote learning because of the lack of technologies needed. According to the report of Worldbank (2021), the Covid-19 pandemic has led to the largest disruption of education systems in decades, with the longest school closures, which has caused substantial losses and inequalities in learning. Jones et al. (2021) examined the effect of the Covid-19 pandemic on access to education for adolescents. They found that the Covid-19 pandemic enhances pre-existing educational inequalities. Favara et al. (2021) showed that school closures due to the pandemic significantly increase learning losses and school dropout rates across the countries. Dreesen et al. (2020) stated that pre-existing social and educational inequalities have risen since the Covid-19 pandemic, given disadvantages in reaching technologies needed for remote learning. Jæger and Blaabæk (2020) examined inequalities in learning during the Covid-19 pandemic. They found that the Covid-19 pandemic enhanced educational inequality because the students with poorer families have fewer learning opportunities than richer ones. Billon et al. (2021) analyzed the effect of educational inequality on Internet access in high and middle-income countries for the period of 2005–2015. They concluded that there is a negative relationship between educational inequality and Internet access, and this effect is more in middle-income countries than in high-income ones.

To this end, the following issues will be the focus of this study:

1. To what extent has the Covid-19 pandemic, which has caused businesses and schools to meet through virtual platforms, affected individual Internet access?
2. How does the economic development level affect individual Internet access?
3. Do the requirements to shift education online because of the Covid-19 pandemic widen educational inequalities?
4. Do inequalities in Internet access and usage affect educational inequality at a national level?

This study contributes to the existing literature in several ways. Some studies are focusing on the effect of Internet access on educational inequality (Asongu et al., 2019; Zhou et al., 2019). The studies investigating how income inequality affects Internet access (Martin and Robinson, 2007; Vincent, 2016) is limited. However, as far as we know, only one study (Billon et al., 2021) examines the impact of educational inequality on Internet access. However, this study examines the educational inequality in terms of Internet access and thus presents both the factors affecting Internet access and the effect of Internet access on educational inequality. In other words, the study exhibit how the disparities in opportunities to the Internet access impact educational inequality during the Covid-19 pandemic. This study also investigates whether effects change in terms of the regional economic development levels. The study is expected to contribute to the literature by investigating the role of the Covid-19 pandemic on the relationship between Internet access and educational inequality. With the acceleration of digitalization in education during the Covid-19 pandemic, the findings are expected to support the policies to reduce educational inequality and therefore, enhance economic development.

Secondly, this study uses spatial panel data models to examine the neighbor relationships between educational inequality and




**Note:** The figure is drawn by the authors.

**Fig. 1.** Moran's I plot for the Internet access and educational inequality in OECD countries.
**Note:** The figure is drawn by the authors.

Internet access. Thanks to this approach, the spatial effects can be included in the models, and how the neighbor regions have influenced the so-called relationship can be presented. This study contributes to the literature by providing evidence on the role of the neighbor relations in regional internet access and educational inequality.

## 2. Theoretical background

Part of the process of integrating the developing countries well with the global economy and increasing their level of development is access to information. Mocnik and Sirec (2010) expressed that Internet access is an important tool for individuals to easily access information. The Internet enhances innovation (Paunov & Rollo, 2016), encourages social interactions among friends and a wider social network (Liang & Guo, 2015) and it also decreases the costs of efficient communication and access to information. (Stevenson, 2008; Beard et al., 2012). Consequently, Internet access significantly affects economic activity, particularly through its impact on productivity and social welfare (Jorgenson et al., 2008).

The studies have highlighted variables such as income level and urbanization (Dasgupta et al., 2001), income per capita, years of schooling, trade openness (Chinn & Fairlie, 2007), education, occupation, age, and employment (Lera-Lopez et al., 2011). Warren et al. (1998) stated that the Internet is an essential information source for academic education. Park (2009) expressed that the Internet allows students to obtain a vast range of education resources anytime and anywhere through online interactive learning, global education programs, and online research.

Internet access can positively influence the quality of education, which is one of the fundamental factors of sustainable economic development, (Ciglaric & Vidmar, 1998; Charp, 2000; Laurillard, 1992). Dryli and Kinnaman (1996) stated that Internet access also provides a means for constructive feedback and overall development for teachers, instructors, and students by letting them think creatively and giving easier access to helpful information (Dryli & Kinnaman, 1996).

The richer countries have well-developed market economies, and so they invest in research and development. Therefore, innovation regarding the Internet more quickly improves in these countries. Innovations in the Internet increase the number of Internet users (Wunnava & Leiter, 2009). Although the Internet has become nearly omnipresent and is now a necessary component of standard education curriculums, some students have little access to the Internet because of their economic situations. Disadvantaged students have families with low-income lack of technological instruments such as computers, mobile phones, the Internet, etc., and they can not effectively use technology (Chapman et al., 2010). Consequently, disadvantaged students are less probably to utilize quality Internet resources for their education and academic development (Zhang, 2015). Thereby, there are difficulties in understanding the ways Internet access or the lack thereof can cause educational inequality.

In the literature, it is emphasized that technology diffusion plays an important role in a social process. As far as the epidemic models of the diffusion theory of innovations, technology diffusion occurs when users have social influence, social learning, or when they are in touch with early adopters (contagion models) (Young, 2009). The diffusion theory of innovations (Rogers, 2003) indicates that users firstly take information about how to use technology. The educational level of the user is important for technology adaptation. Similarly, heterogeneity models (Rosenberg, 1972) state that socioeconomic factors such as educational level are significant to clarify the differences in technology adoption (Karshenas & Stoneman, 1995; Geroski, 2000). Likewise, some of the economics literature has shown the significance of human capital to adopt new technologies (Nelson & Phelps, 1966; Rosenberg, 1972; Benhabib & Spiegel, 2005). Thereby, educational level is an important determinant of Internet use (Bonfadelli, 2002; Robles & Torres-Albero, 2012; Scheerder et al., 2017). Besides, educational inequality may affect the communication flows between Internet users. Educational inequality could inhibit the users from gaining advantages of Internet diffusion on economic growth (Billon et al., 2018). The theory of the social shaping of technology indicates that technology use is formed by individuals' socioeconomic properties (MacKenzie and Wajcman, 1999; Williams & Edge, 1996). This can be explained by technology diffusion as a consequence of supply and demand factors representing the economic and social development levels of countries. In this sense, the educational levels of individuals affect technology use. (Karshenas & Stoneman, 1995; Comín & Mestieri, 2014). Asongu et al. (2019) investigate the relationship between inequality, Information and Communication Technology, and education in sub-Saharan African countries. Billon et al. (2021) examine how educational inequality impacts Internet access for 69 high-and-middle income countries. They find that there is a negative relationship between Internet access and education inequality and that socioeconomic attributes such as the level of education and the distribution of formal education are important variables in explaining Internet access. Martinez-Dominguez and Fierros-Gonzales (2022) analyze the determinant of Internet access for school-age children in Mexico. They show that Internet access and usage patterns base on the level of education, socioeconomic status, digital skill, and the existence of electronic devices in the household. Consequently, educational inequality should be taken into account to explain the factors of Internet access.

## 3. Data, methodology, and models

### 3.1. Data

To determine factors affecting individual Internet access in OECD countries[1] from 2005 to 2020, we suggest an empirical model

[1] 35 OECD countries which are Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxemburg, Mexico, Netherlands, New Zeland, Norway, Poland, Portugal, Slovak, Slovenia, Spain, Switzerland, Sweden, Turkey, United States, United Kingdom are included in the analysis.

taking into account the ratio of Internet users to the total population. This model also includes socioeconomic and macroeconomic variables comprising GDP per capita, the GINI index, the unemployment rate, the youth unemployment rate, the population under 15 years of age, the population over 65, the primary school enrollment, the secondary school enrollment, the tertiary school enrollment, and the urban population. The ratio of Internet users to the total population is used to represent Internet access (Mocnik & Sirec, 2010; Vincent, 2016; Rodriguez-Crespo and Zarzoso, 2019; Billon et al., 2021). The variables used in this study are given in Table 1.

The theoretical expectations regarding the determinants of Internet access are as follows: There is an expectation of a positive relationship between GDP per capita and Internet access given that a rise in income increases Internet access by affecting the demand for the Internet. GDP per capita is an indicator for development level of a country. The countries with higher GDP per capita have capability to invest more in research and development, and innovation regarding the Internet (Chaudhuri et al., 2005; Wunnava & Leiter, 2009; Chinn & Fairlie, 2007; Cruz-Jesus et al., 2017). The unemployed have more difficulty in purchasing and acquiring Internet service; and thus, their Internet access is expected to decrease. So, the unemployment rate is assumed to be a negative relationship with Internet access (Chaudhuri et al., 2005). Similarly, the GINI coefficient is expected to be a negative correlation with Internet access due to the fact that fewer people have ability to pay subscription and connection fees as income inequality in a country increases (Chaudhuri et al., 2005; Wunnava & Leiter, 2009). The younger generations with a higher level of education research more information on the web and therefore they use more the Internet. Thus, a positive relationship is expected between education level and Internet access. We include primary, secondary, and tertiary enrollments in the dataset (NTIA, 2002; Chaudhuri et al., 2005). It is expected that Internet access is positively correlated with the population under 15 years of age and negatively correlated with the population aged 65 and over. Larger urban populations tend to have cheaper cost on the Internet because of lower subscriber costs, which cause higher Internet access (Koski & Kretschmer, 2005). Information and communication technology (ICT) is an indicator of the communication technology size in a country. Therefore, higher ICT net exports are expected to increase Internet access. In other words, there should be a positive relationship between ICT net exports and Internet access (Vincent, 2016, Billon et al., 2021). To measure the effectiveness of the Covid-19 pandemic on internet access, we include a dummy variable called "COVID", whose value is 1 for 2020 and 0 for the other years. Due to restrictions and lockdown policies to control the spread of the Covid-19, it is expected that Internet access has increased around the world for reasons such as businesses and schools meeting through online platforms and the extended amount of time people are staying at home.

Another aim of this study is to analyze the effects of Internet access and the Covid-19 pandemic on educational inequality. The data for educational inequality from the reports of the United Nations Development Programme (UNDP). The UNDP defines educational inequality as inequality in the distribution of the average years of schooling. This study suggests an empirical model with the explanatory variables including income inequality, inequality in life expectancy, GDP per capita, the ratio of urban population to the total population, average number of years of education received by people age 25 and older, the ratio of tertiary education expenditures to government expenditure, tertiary enrollment rate, and Internet access. For this analysis, the variables used in this study are given in Table 2.

The theoretical expectations regarded to the determinants of educational inequality are as follows: The average years of schooling are expected to be negatively correlated with educational inequality. The urban population is expected to have a nonlinear effect on educational inequality. So, the square of this variable is included in the model. A positive relationship between low income and educational inequality is also expected. The ratio of tertiary education expenditures to government expenditures, the tertiary enrollment rate, and the GDP per capita is expected to be negatively correlated with educational inequality. A negative relationship between Internet access and educational inequality is expected. The reason is that disadvantaged students in poor families may be less likely to access the Internet to improve their education, which is based on Bourdieu's observations (Gregorio and Lee, 2002). ICT is a driving factor of economic growth and encourages education, healthcare, social change, and national development (Beardon, 2005; Mocnik & Sirec, 2010). The disparities in ICTs access create different types of digital divides. The so-called divides may cause social inequalities such as educational inequalities (Robinson et al., 2015). Thus, a negative relationship between ICT net exports and educational inequality is expected.

### 3.2. Methodology

The subject of geography was first proposed by W. Tobler (1979). Tobler said that (Tobler, 1979: 379):

> "Everything is related to everything else, but near things are more related to distant things".

Spatial data analysis is an econometric approach based on spatial data. The concept of spatial effect stands out in this approach. The spatial effect includes both spatial heterogeneity and spatial dependence (LeSage & Pace, 2009: 17; Anselin, 1988, p. 11).

Spatial dependence or spatial autocorrelation are the main issues of spatial econometrics. Spatial autocorrelation occurs as a consequence of the existence of a functional relationship between what happens at any point in space and what happens in other regions. The value of a variable in a spatial location is explained not only by endogenous conditions but also by the value of the same variable in its other neighbor locations (Frexedas and Vaya, 2005: 154).

The value of x in region i depends on the conditional probability of its value in neighbor region j.

$$P[x_i / x] = P[x_i / x_j] \tag{1}$$

$$Cov(x_i, x_j) = E(x_i, x_j) - E(x_i)E(x_j) \neq 0 \tag{2}$$

**Table 1**
Description of the variables for determining Internet access.

| Independent variable | Description | Source |
|---|---|---|
| | COVID | Dummy Variable |
| | Log of GDP per capita | World Databank |
| | Unemployment rate | World Databank |
| | GINI Index | World Databank |
| | Population under 15 years | World Databank |
| | Population age 65 and over | World Databank |
| | Primary enrollment gross | World Databank |
| | Gross secondary school enrollment | World Databank |
| | Gross tertiary school enrollment | World Databank |
| | Urban population growth | World Databank |
| | Square of urban population growth | World Databank |
| | ICT net exports (ICT goods exports – ICT goods imports) (% of total goods exports-imports) | World Databank |
| | Fixed broadband subscriptions | World Databank |
| **Dependent Variable** | Individual Internet Access | World Databank |

**Table 2**
Description of variables used to determine educational inequality.

| | Description | Source |
|---|---|---|
| **Independent variable** | Internet access | World Databank |
| | COVID | Dummy variable |
| | GINI index | World Databank |
| | Inequality in life expectancy | United Nations Development Programme Human Development Reports |
| | Log of GDP per capita | World Databank |
| | Gross tertiary school enrollment | World Databank |
| | Average years of schooling | United Nations Development Programme Human Development Reports |
| | Urban population growth | World Databank |
| | Square of urban population growth | World Databank |
| | The ratio of public expenditure on tertiary education to GDP | World Databank |
| | ICT exports (% of total goods exports) | World Databank |
| **Dependent Variable** | Education inequality | United Nations Development Programme Human Development Reports |

$\forall i \neq j \in J$

The spatial weight matrix is used to insert spatial effect in the model. The spatial weight matrix is a positive and symmetric matrix with nxn dimension and is denoted by W.

$$W = \begin{bmatrix} w_{11} & \dots & w_{1n} \\ w_{21} & w_{22} & w_{2n} \\ \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & w_{nn} \end{bmatrix} \tag{3}$$

The weight matrix is standardized so that the sum of rows is 1. All elements of the matrix with row standardized are equal, which enables all weights to be between 0 and 1 and indicates the average value of neighbor regions (Ullah and Giles, 1998, p. 258). The model may include a spatial autoregressive process in error term or spatial lagged dependent variable in case of spatial dependence between observations. The first model is called the spatial error model, the second is the spatial lag model (Elhorst, 2003: 245). If spatial independent variables in addition to spatial lagged dependent variables are included in the model, then it is defined as the spatial Durbin model. The so-called models are as follows (Elhorst, 2003: 249, Mur & Angulo, 2006, p. 209):

Spatial lag model

$$Y_t = pWY_t + X_t\beta + \mu + \varepsilon_t\ ,\ E(\varepsilon_t) = 0,\ E\left(\varepsilon_t, \varepsilon_t'\right) = \sigma^2 I_N \tag{4}$$

Spatial error model

$$Y_t = X_t\beta + \mu + \varnothing_t \tag{5}$$

$$\varnothing_t = \delta W \varnothing_t + \varepsilon_t\ ,\ \mathrm{E}(\varepsilon_t) = 0, E\left(\varepsilon_t, \varepsilon_t'\right) = \sigma^2 I_N$$

Spatial Durbin model

$$Y_t = pWY_t + X_t\beta + \varphi WX_t + \varepsilon_t \ , \ E(\varepsilon_t) \ = \ 0, \ E\left(\varepsilon_t, \varepsilon_t^{'}\right) = \sigma^2 I_N \tag{6}$$

In the above models, W is the weight matrix, $\delta$ is the spatial autocorrelation coefficient, $\varphi$ indicates the spatial cross-regressive parameter and ρ is the spatial autoregressive parameter. $\varepsilon_{it}$ is assumed to be normally distributed independently of the explanatory variable with a zero mean and a constant variance.

### 3.3. Spatial dependence in the internet access model

This study aims to investigate the determinants of Internet access and the effect of the Covid-19 pandemic on it. The research question addresses to what extent the Covid-19 pandemic, which has caused businesses and schools to meet through virtual platforms, has affected individual Internet access. For this purpose, an empirical model reflecting the socio-economic and macroeconomic determinants of Internet access at a national level is proposed. The model for Internet access is as follows:

$$Internet\ Access_{it} = \alpha_0 + \sum_{i=1}^{q} \alpha_i Z_{it} + \omega\ COVID + \varepsilon_{it} \tag{7}$$

Internet access reflects the ratio of Internet users to the total population. $Z_{it}$ indicates the explanatory variables including GDP per capita, the inflation rate, the GINI coefficient, the unemployment rate, the youth unemployment rate, the population under age 15, the population age 65 and over, the primary school enrollment, the secondary school enrollment, the tertiary school enrollment, and urban population.

Spatial effects are considered to examine the effects of contiguity on Internet access. Thus, the following spatial panel data models are used (Anselin, 1988, pp. 14–15):

Spatial lag model

$$Internet\ Access_{it} = a_{1,0} + \sum_{i=1}^{q} \gamma_{1,i} Z_{it} + p_1 WInternet\ Usage_{it} + \omega_1\ COVID + \varepsilon_{1,it} \tag{8}$$

Spatial error model

$$Internet\ Access_{it} = a_{2,0} + \sum_{i=1}^{q} \gamma_{2,i} Z_{it} + \omega_2\ COVID + \tau_{it} \tag{9}$$

$$\tau_{it} = \delta W \tau_{it} + \varepsilon_{2,it}$$

Spatial Durbin model

$$Internet\ Access_{it} = a_{3,0} + \sum_{i=1}^{q} \gamma_{3,i} Z_{it} + p_2 WInternet\ Usage_{it} + \varphi_1 \sum_{i=1}^{q} W_{ij} Z_{it} + \omega_3\ COVID + \ \varepsilon_{3,it} \tag{10}$$

In these models, W indicates the weight matrix, $\delta$ is the spatial autocorrelation coefficient, $\varphi$ is the spatial cross-regressive parameter and ρ is the spatial autoregressive parameter. It is assumed that $\varepsilon_{it}$ is normally distributed independently of the explanatory variable with a zero mean and a constant variance. In the case where spatial effects are present, the least square method is not appropriate. Thus, the spatial panel data models are estimated by using the maximum likelihood method.

### 3.4. Spatial dependence in the educational inequality model

To investigate the impact of Internet access on educational inequalities, an empirical model is used that evaluates Internet access with control variables that reflect socio-economic effects. This model is used to highlight possible educational inequalities at a national level. The following equation is the reference model for educational inequality:

$$G_{it}^{EDUCATION} = \vartheta_0 + C_1 Internet\ Access_{it} + \sum_{i=1}^{q} \theta_i Z_{it} + \Phi\ COVID + \varepsilon_{it} \tag{11}$$

In the model, the subscripts $i$ and $t$ are the country and time period respectively. $G^{EDUCATION}$ reflects educational inequality at a national level and $Z_{it}$ indicates the control variables that include the GINI index, GDP per capita, inequality in life expectancy, average years of schooling, the ratio of urban population to the total population, the ratio of tertiary education expenditures to total government expenditures and gross tertiary school enrollment rate. COVID indicates the dummy variable whose value is 1 for the Covid-19 period and 0 for the other years.

Spatial effects are considered in this study to assess the factors that explain the various changes in educational inequality between the different regions. For this purpose, Eq. (11) is estimated using the following spatial panel data models (Anselin, 1988, pp. 14–15):

Spatial lag model

$$G_{it}^{EDUCATION} = \vartheta_{1,0} + \complement_2 Internet\ Access_{it} + \sum_{i=1}^{q} \theta_{1,i} Z_{it} + p_3 W G_{it}^{EDUCATION} + \Phi_1\ COVID + v_{1,it} \tag{12}$$

Spatial error model

$$G_{it}^{EDUCATION} = \vartheta_{2,0} + \complement_3 Internet\ Access_{it} + \sum_{i=1}^{q} \theta_{2,i} Z_{it} + \Phi_2\ COVID + u_{it} \tag{13}$$

$$u_{it} = \delta W u_{it} + v_{2,it}$$

Spatial Durbin model

$$G_{it}^{EDUCATION} = \vartheta_{3,0} + \complement_4 Internet\ Access_{it} + \sum_{i=1}^{q} \theta_{3,i} Z_{it} + p_4 W G_{it}^{EDUCATION} + \varphi_2 W Internet\ Access_{it} + \varphi \sum_{i=1}^{q} W_{ij} Z_{it} + \Phi_3\ COVID + v_{3,it} \tag{14}$$

As before, W indicates the weight matrix, $\delta$ is the spatial autocorrelation coefficient, $\varphi$ is the spatial cross-regressive parameter and ρ is the spatial autoregressive parameter. It is assumed that $v_{it}$ is normally distributed independently of the explanatory variable with a zero mean and a constant variance.

In the case where educational inequality is present, the spatial spread effect occurs through indirect mechanisms. Even in situations where substantial information is disseminated, there is an intermediary mechanism known as the interregional transfer of human capital. Therefore, in the presence of spatial effects, it is again not appropriate to use the least-squares method. Because the spatial error model includes the autocorrelation and heteroscedasticity problems, the least-squares estimators are unbiased, but they lose the assumption of efficiency. In addition, the least-squares estimators are both biased and inconsistent because the spatial lag model has the lagged dependent variable. Therefore, the maximum likelihood method can overcome these problems by estimating the model coefficients with nonlinear optimization methods based on the log-likelihood function (Anselin, 1988, pp. 58–59; Anselin and Hudak, 1992: 511).

### 3.5. Exploring spatial dependence

The first step of the spatial analysis is to test whether there is spatial dependence. Spatial dependence (or spatial correlation) is defined as the presence of a functional relationship between the events in a region with ones in its neighboring regions. In this study, a spatial weight matrix was created based on border contiguity to test spatial dependence. The lag operator is used to include the spatial dependence factor in the model. It expresses a weighted mean of random variables in neighboring regions. Positive spatial autocorrelation occurs when similar values relating to a variable are spatially clustered while negative spatial autocorrelation occurs when dissimilar values are clustered in an area. Regional clusters are present when there is a positive spatial autocorrelation. However, regional outliers appear when there is a negative spatial autocorrelation.

We test global spatial autocorrelation by using Moran's I statistic for Internet access and educational inequality. This statistic is outlined as follows:

$$I = \left(\frac{n}{s_0}\right) \frac{\sum_i^n \sum_j^n w_{ij} x_i x_j}{\sum_i^n x_i^2} \tag{15}$$

where n is the number of economic areas, $w_{ij}$ is the value shown in the spatial weights matrix which takes a value of 1 if areas $i$ and $j$ are border neighbors and 0 otherwise. $s_0 = \sum_i \sum_j w_{ij}$ Moran's I statistic takes a value of $-1$ if there is a negative spatial autocorrelation and 1 if there is a positive spatial autocorrelation. If neighboring areas take similar values, Moran's I statistic tends to be positive (LeSage & Pace, 2009, p. 155).

In light of this information, Moran's I statistics relating to Internet access and educational inequality are calculated to evaluate the spatial autocorrelation between 2005 and 2020. The results are given in Table 3.

Obtaining the statistical significance for Moran's I statistic requires a randomization process since both Internet access and educational inequality are non-normally distributed. The results in Table 3, which indicate spatial autocorrelation, are statistically significant for both Internet access and educational inequality each year. From the results, it is clear that spatial dependence in the distribution of both regional Internet access and regional educational inequality is positive. Positive spatial dependence reflects spatial clustering of similar values. In other words, high Internet access areas are followed by other high Internet access areas (or low Internet access areas are followed by low Internet usage areas). A similar result was found for educational inequality. Thus, the observations of both regional Internet access and regional educational inequality in OECD countries are spatially related, which indicates that the observations in question are dependent.

In light of the LM tests that test spatial dependence in the model for Internet access and educational inequality, the estimations of the fixed-effect model without spatial effects reflect misspecification because of omitted spatial dependence. When spatial dependence is present, the models must be estimated by maximum likelihood estimators to take into account the assumptions of the BLUE estimator (Anselin, 1988; Anselin & Bera, 1998; Elhorst, 2010; LeSage & Pace, 2009).

## 4. Empirical results

The results of the model related to Internet access will be given first, then the results of the model related to educational inequality.

### *4.1. Spatial dependence models for internet access*

Table 4 shows the results of the fixed-effect panel data model and the spatial panel data model for Internet access. According to this analysis, both the LM test for spatial dependence and its robust version have statistically significant values. However, the LM error test statistic and its robust version are not statistically significant. This result shows that the spatial lag dependence model should be taken into account to decide on the appropriate model, which means that Internet access in a region is influenced by the Internet access of its neighbors.

The estimated results of the spatial effects can be summarized by the following: GDP per capita has a positive impact on Internet access, which means that the higher income level the countries have the higher their Internet access is. This is because increases in income level stimulate demand for Internet access. Unemployment rates create an adverse impact on Internet access by decreasing income levels. Similarly, the GINI index, which shows income inequality, negatively influences Internet access due to its distorting effect on income distribution. If it is drawn attention to school enrollment, gross secondary school enrollment provides a positive contribution to Internet access, but the gross primary enrollment rate diminishes it. The so-called situation exhibits that although the students in primary school have little need of Internet access, individuals are in more need of the Internet for their self-improvement when the education level rises. The Internet access among those 65 and over in the population is significantly less than among those who are younger. Fixed broadband subscriptions have a positive impact on internet access. Finally, the study found that the COVID-19 pandemic has increased Internet access particularly because businesses and education programs have moved online.

**Table 3**
Spatial autocorrelation of Internet access and educational inequality (2005–2020).

| Year | Internet Access | | | | Educational Inequality | | | |
|---|---|---|---|---|---|---|---|---|
| | Morans' I | E(I) | SD(I) | p-value | Morans's I | E(I) | SD(I) | p-value |
| 2005 | 0.14152 | −0.02941 | 0.09063 | 0.0592 | 0.27231 | −0.0294 | 0.08469 | 0.0003 |
| 2006 | 0.14681 | −0.02941 | 0.09010 | 0.0505 | 0.27231 | −0.0294 | 0.08469 | 0.0003 |
| 2007 | 0.13085 | −0.02941 | 0.08982 | 0.0743 | 0.27231 | −0.0294 | 0.08469 | 0.0003 |
| 2008 | 0.12558 | −0.02941 | 0.08931 | 0.0826 | 0.27231 | −0.0294 | 0.08469 | 0.0003 |
| 2009 | 0.14549 | −0.02941 | 0.08919 | 0.0498 | 0.27231 | −0.0294 | 0.08469 | 0.0003 |
| 2010 | 0.15144 | −0.02941 | 0.08904 | 0.0422 | 0.27231 | −0.0294 | 0.08469 | 0.0003 |
| 2011 | 0.19517 | −0.02941 | 0.08947 | 0.0120 | 0.26378 | −0.0294 | 0.08624 | 0.0006 |
| 2012 | 0.17342 | −0.02941 | 0.08919 | 0.0229 | 0.26994 | −0.0294 | 0.08612 | 0.0005 |
| 2013 | 0.20039 | −0.02941 | 0.08936 | 0.0101 | 0.38771 | −0.0294 | 0.08455 | 0.0000 |
| 2014 | 0.20530 | −0.02941 | 0.08905 | 0.0084 | 0.39635 | −0.0294 | 0.08528 | 0.0000 |
| 2015 | 0.22485 | −0.02941 | 0.08969 | 0.0045 | 0.41423 | −0.0294 | 0.08432 | 0.0000 |
| 2016 | 0.18546 | −0.02941 | 0.08930 | 0.0161 | 0.38377 | −0.0294 | 0.08963 | 0.0000 |
| 2017 | 0.14304 | −0.02941 | 0.08963 | 0.0543 | 0.39721 | −0.0294 | 0.08939 | 0.0000 |
| 2018 | 0.16440 | −0.02941 | 0.09001 | 0.0313 | 0.10886 | −0.0294 | 0.08929 | 0.1220 |
| 2019 | 0.12191 | −0.02941 | 0.09003 | 0.0928 | 0.19228 | −0.0294 | 0.08843 | 0.0121 |
| 2020 | 0.11715 | −0.02941 | 0.08944 | 0.1013 | 0.19228 | −0.0294 | 0.8843 | 0.0121 |

E(I): Expected value of Moran's I statistics.
SD(I): Standard deviation of Moran's I statistics.
Note: Morans' I statistics are calculated for all independent variables in addition to the dependent variables and these statistics are obtained significantly.

**Table 4**
The Estimation results for spatial dependence models of the Internet access.

| Variable | Non-Spatial Model | Spatial Lag Model |
|---|---|---|
| COVID | 2.46985*** (0.88032) | 1.407067*** (0.682647) |
| Log of GDP per capita | 20.08285*** (1.950024) | 8.100251*** (1.692008) |
| GINI index | 0.167863 (0.15672) | −0.20563* (0.117329) |
| Unemployment rate | −0.346026*** (0.082312) | −0.16844*** (0.065058) |
| Population under 15 years | 8.915445*** (1.767962) | 1.881658** (1.079903) |
| Population age 65 and over | −9.128284*** (1.643008) | −4.769291*** (1.288886) |
| Gross primary school enrollment | −0.31304*** (0.061924) | −0.1407*** (0.048989) |
| Gross secondary school enrollment | 0.034479 (0.027491) | 0.033276* (0.020817) |
| Gross tertiary school enrollment | 0.233104*** (0.02841) | 0.054954*** (0.023084) |
| Urban population growth | 1416.819*** (296.9223) | 715.1573*** (222.5643) |
| Square of urban population growth | −156.547*** (34.70967) | −82.9157*** (25.97406) |
| Fixed broadband subscriptions | 25.96141*** (1.777532) | 6.860089*** (1.455959) |
| **Spatial Effects** | | |
| Spatial lag (*p*) | – | 0.694395*** (0.033899) |
| LM-lag | 21.1383*** | – |
| LM-error | 0.0677 | – |
| Robust LM-lag | 22.2468*** | |
| Robust LM-error | 1.1762 | - |
| R-square | 0.8893 | 0.9725 |
| Log-likelihood | −1501.042 | −1486.1507 |

Notes: The values in the parenthesis indicate standard error. ***,**, and * indicate a statistical significance of 1%, 5%, and 10% levels, respectively. LM is the Lagrange Multiplier test. ICT good exports were initially included in the model, but it is removed for lacking statistical significance.
Spatial error and spatial Durbin models were estimated, but the estimation results for the spatial lag model are reported depending on the results of spatial LM tests.

### 4.2. Spatial dependence models for measuring educational inequality

Table 5 exhibits the results related to the fixed-effect panel data model and the spatial panel data model for educational inequality. The results for both the LM lag and the LM error spatial dependence tests for educational inequality indicate that the spatial dependence must be taken into account. If the spatial dependence is not considered, the estimators will be biased and inconsistent. Both the LM lag test statistic and its robust versions are statistically significant while the LM error test statistic and its robust version are not statistically significant. These results represent that the spatial lag dependence model is valid, which means that educational inequality in a region is influenced by educational inequality in its neighbors.

The estimation results of the spatial effect model can be summarized by the following: There is a negative relationship between

**Table 5**
The Estimation results for spatial dependence models for educational inequality.

| Variable | Non-Spatial Model | Spatial Lag Model |
|---|---|---|
| Internet Access | −0.038924* (0.021411) | −0.061192*** (0.010918) |
| COVID | −0.26441 (0.492149) | 0.49622*** (0.263145) |
| Inequality in life expentancy | 0.704727*** (0.202936) | 0.626228*** (0.10013) |
| Log of GDP per capita | −1.70938 (1.272179) | −1.21945** (0.638802) |
| Gross tertiary school enrollment | 0.070241*** (0.018752) | 0.034827*** (0.009416) |
| Average years of schooling | −0.06334 (0.374064) | −0.48854*** (0.180206) |
| Urban population growth | 108.5156 (104.9892) | 131.4817*** (55.00845) |
| Square of urban population growth | 663.1129 (11137.8) | −11359.7 (5878.24)** |
| The ratio of public expenditure on tertiary education to GDP | −0.0306 (0.045798) | −0.04274* (0.023613) |
| ICT goods exports (% of total goods exports) | −0.27412 (0.389419) | −0.538861*** (0.183145) |
| **Spatial Effects** | | |
| Spatial lag (*p*) | – | 1.00208*** (0.027591) |
| LM-lag | 2.9770** | – |
| LM-error | 0.2633 | - |
| Robust LM-lag | 3.8608** | – |
| Robust LM-error | 1.1472 | - |
| R-square | 0.2521 | 0.8068 |
| Log-likelihood | −1309.213 | −1022.7576 |

Notes: The values in the parenthesis indicate standard error. ***,**, and * indicate a statistical significance of 1%, 5%, and 10% levels, respectively. LM is the Lagrange Multiplier test. GINI index and fixed broadband subscriptions were initially included in the model, but they were removed for lacking statistical significance. Spatial error and spatial Durbin models were estimated, but the estimation results for the spatial lag model are reported depending on the results of spatial LM tests.

Internet access and educational inequality. Because the education programs have generally shifted to online platforms, Internet access has become much more important for the students. Therefore, an increase in Internet access reduces educational inequality. The COVID-19 pandemic causes educational inequality to increase. Students from poor or disadvantaged backgrounds suffer from limited access to technology. As the educational system quickly moved online due to the Covid-19 crisis, the disparity of educational opportunities among many students deepened.

The COVID-19 pandemic quickly turned from a health crisis into an economic crisis which caused the income distribution levels to deteriorate. Depending on this situation, educational inequality for the poor or disadvantaged students becomes more pronounced. Inequalities in life expectancy are also positively correlated to educational inequality, but GDP per capita is negatively correlated. The average years of schooling have a positive effect on educational inequality. The impacts of urban population growth and the square of urban population growth on educational inequality are respectively positive and negative, respectively, which indicates that the effects of urban population on educational inequality are inverted-U shaped. The ratio of public expenditures on tertiary education to GDP has a reducing effect on educational inequality. An increase in ICT goods exports allows for reducing educational inequality.

## 5. Discussion

From the findings of this study, it is concluded that the policies relevant to free Internet access, such as establishing free wifi centers in rural and urban areas, the Internet and the technological devices used free of charge in public areas or even technology offices established in the provinces/regions with low income should be implemented to provide a positive impact on the economy. These technology facilities provide training and education to use or produce the most imported technological products or provide training for the production of intermediate goods and raw materials, which are mostly used in technology. This type of technical training has the potential to increase the level of a skilled and qualified workforce in a region. At the same time, they do not need to be limited to places operating in areas such as municipal buildings, youth centers, or universities, but can expand to areas not yet reached. In this context, import and export agreements with countries that have similar geographical features or have similar technological needs, especially for technology and information transfer, could be quite advantageous. Similarly, new perspectives should be imagined for reaching out to new communities without a colonial mindset. Perspectives that envision a phenomenon of "sharing" that transfers resources from the affluent to the poor, where the economic surplus' of developed countries can be transferred to undeveloped or underdeveloped countries. In addition, countries that have developed innovations in science and technology should develop projects to offer free education to underdeveloped communities in their own countries. Import and export policies could apply tariff reductions to countries that agree to transfer knowledge in the fields of education, healthcare, and technology.

For the policies specifically relating to education, there are two important points to be considered. First, an innovative and community-oriented education system should not limit training to only brick and mortar buildings in which the infrastructure is already in place, but also it is provided training in small social facilities or even in open outdoor areas. Second, the selection of the trainers should be directed based on the performance indicators from the institutions providing training. Consequently, this may lead to a competitive and innovative environment in the education community.

Considering that Internet networks are inadequate and new infrastructure for this is costly and will take considerable time, a short-term solution may be the free use of free frequencies, especially for satellite frequencies. In the field of education, in particular, an integrated system of allocating separate channels for each course at each level to eliminate potential disruptions can be effective. Agreements between representatives of alternative distance learning platforms and global organizations can provide access to cloud technology for economically underdeveloped countries. Through global server networks, countries can create a video course archive by providing sufficient network capacity with end-to-end encryption technology. Furthermore, by translating these archives into different languages students can access more comprehensive educational materials.

The digitalization process that began with 'Industry 4.0' or the fourth industrial revolution as it is often called, will certainly affect the education sector as well. In the not too distant future, distance learning will become more widespread than formal education. Therefore, it is necessary to establish the appropriate technological facilities and a level of sufficient coordination with other countries that are necessary to not allow educational inequalities to deepen. The experiences of the Covid-19 pandemic have shown many of the underlying deficiencies that a proactive and innovative education system could address.

## 6. Conclusion

Despite the different conditions in each country, many countries have seen how valuable "information sharing" can be even beyond the Covid-19 pandemic. Due to the restriction policy implemented to control the spread of the virus, individuals turned to the resources of the Internet for socialization in place of common social activities. The use of online technological tools shows that a new stage of the "technological age" has been entered.

While knowledge and technology have become a major focus, many communities have focused on the inequalities related to them. But beyond the traditional categories of economic inequality, the concept of "educational inequality" has emerged in discussions of class distinctions. The new required direction for education, which has highlighted the infrastructure problems for distance learning, created uncertainty in instructor's performances, and uncertainty for the inexperienced students to quickly adapt to a new system, has caused a new dimension of education inequality in the current system. The low-income families with many children, for example, are often left to choose which child will be able to attend their online lesson in the same home. These are new problems leading to a search for new solutions. From the students who cannot attend lessons because they cannot access the Internet to their parents who cannot purchase tablets, the governments and institutions are trying to find quick and simple solutions. This study supports the idea that increasing access to the Internet and technology will help eliminate education inequality. To this end, this study aims to present Internet access and the educational inequalities of different countries by looking at educational opportunities specific to OECD countries.

The empirical findings show that the Covid-19 pandemic has further exposed and deepened many social inequalities and vulnerabilities. The Covid-19 pandemic has caused educational inequalities, in particular, to deepen as well. Increasing the level of income per capita and reducing income inequality positively affect the level of the Internet access necessary to reduce educational inequality. When the development levels increase in a country, Internet access rises and educational inequality declines. An increase in Internet access due to the improvement of individual income levels reduces the extent and effects of educational inequality. Likewise, fixed broadband subscriptions are also observed to increase Internet access. Furthermore, information and communication technology are also significant. An increase in these types of exports allows greater access to the education resources for the students, which causes educational inequality to shrink. When the results are evaluated in terms of rural-urban populations, it is seen that the urban population has an inverted U-shaped effect regarded to both Internet access and educational inequality. When considering the results regarding the education levels, it is concluded that the higher levels of education are correlated with an increase in Internet access and a decrease in educational inequality. The findings of the study support the studies of Dreesen et al. (2020), Favara et al. (2021), and Billon et al. (2021).

It is crucial for the policies to increase Internet access to develop a decrease in educational inequality in a country. The authorities should design the public policies by considering not only the supply and demand for Information and Communication Technologies (ICT) but also their role in educational inequalities. The policies to increase Internet access and diffusion will provide to reduce educational inequalities.

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**Özge Korkmaz** is an associate professor at Malatya Turgut Özal University, Turkey. She has been awarded several national and international prizes. She has been referred to in many national and international journals. She has published on a wide range of topics, including energy economics, applied macroeconometrics, and financial econometrics.

**Elif ERER** is an independent researcher. She graduated from the Ege University doctorate program in economics. She is an economist with technical skills on the econometric modelling of the economy through time series models. Her current research agenda is focused on using these skills to construct models of macroeconomic subjects such as inflation, growth, unemployment rate, monetary and fiscal policies.

**Deniz ERER** is an independent researcher. She graduated from the Ege University doctorate program in economics. She is an economist having the technical skills on econometric modelling and applied econometrics. Her research areas are exchange rates, international trade, international financial markets, monetary policy.